The Accuracy of Monitoring Stress from Wearable Devices Background and Objective References

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The Accuracy of Monitoring Stress from Wearable Devices

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Background and Objective

Continuous monitoring of behaviors as well as physiological and mental states is increasingly considered to be a key prerequisite for optimizing health interventions.

For example, since stress has important implications for a wide variety of health conditions, there is a clear need for new tools to monitor stress in real time to provide tailored and timely interventions.

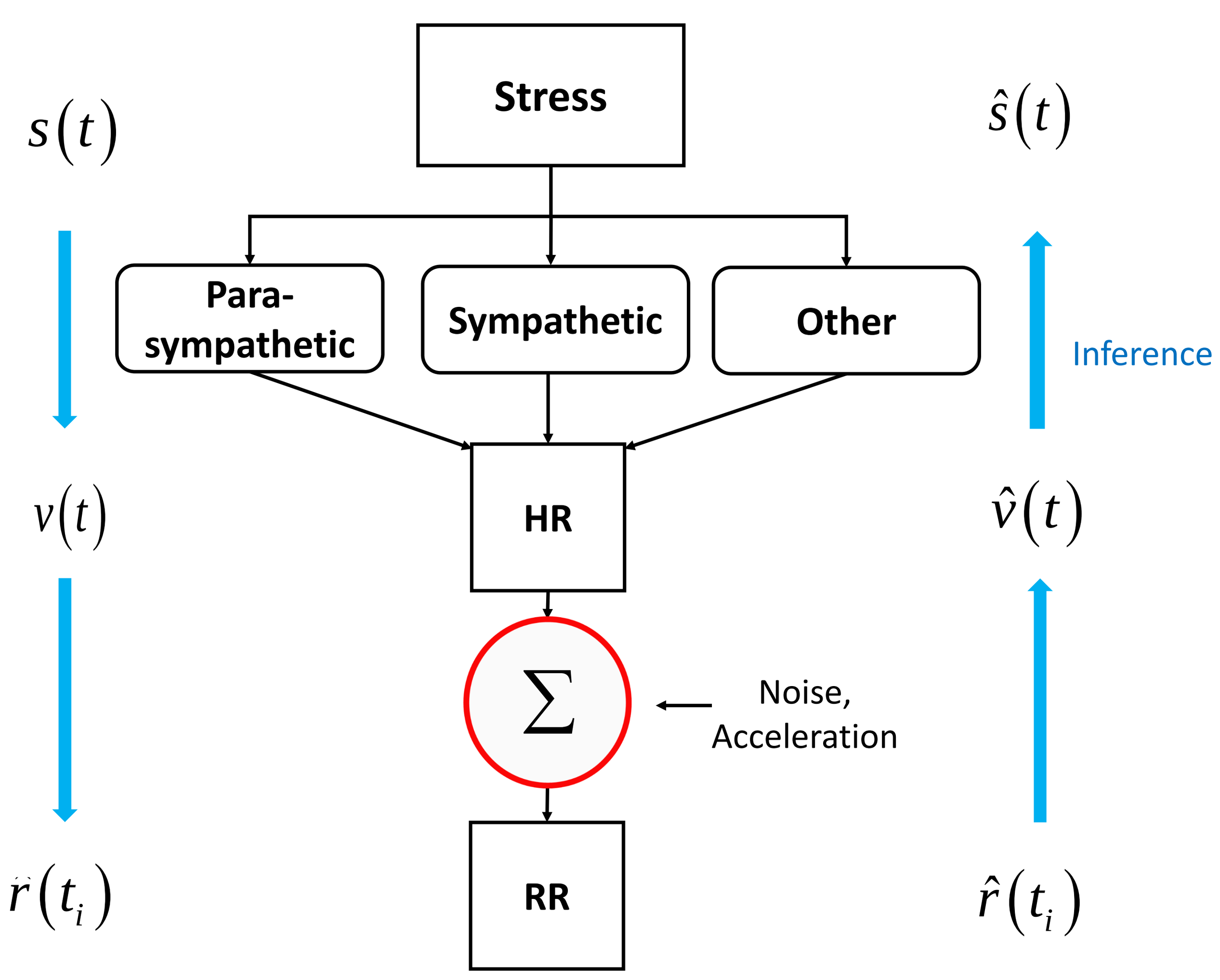
New, affordable wearable sensors may enable continuous and unobtrusive assessment of individuals' health and stress in ambulatory settings. However, data captured by such sensors is typically very noisy. Traditional data cleaning approaches, e.g., simple outlier removal, are inappropriate for such data because they strongly distort subsequent frequency analysis.

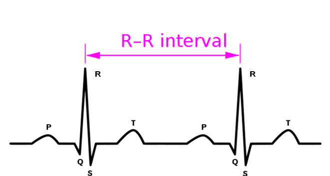
The focus of this work is on assessing the quality of data collected by two wearable wrist sensors and investigating a new algorithm to improve it enough for these sensors to be valuable for ambulatory stress monitoring.

Methodology

Modeling

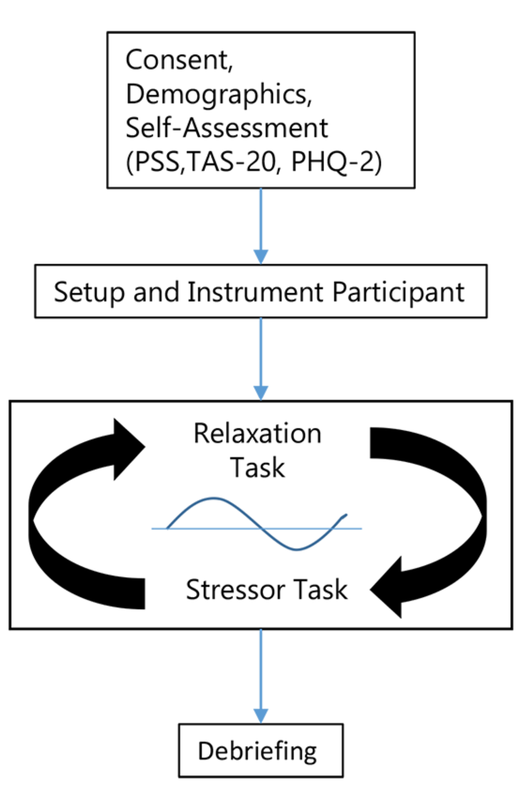
Computational model-based approach
- Model of Stress Effects on HR Function
- HR is assumed to be a continuous function





Study design

Participants: 8 males, 1 female (ages 18 – 52)

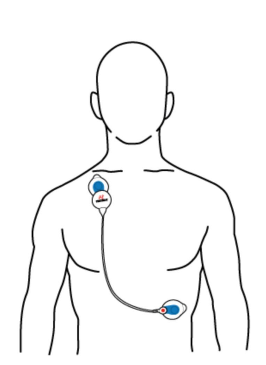


Relaxation:
- Calming music
- Dark room

Stressors:
- International Affective Picture System
- physical activity (marching with arms swinging and stationary biking with arms held still)
- Stroop task,
- Mental arithmetic with distracting background noise

Equipment

FirstBeat - ECG sensor - "gold standard"



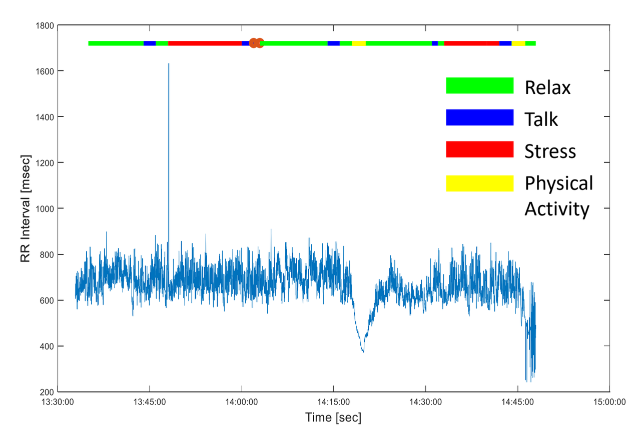
Microsoft Band 2 - PPG sensor - "consumer grade"

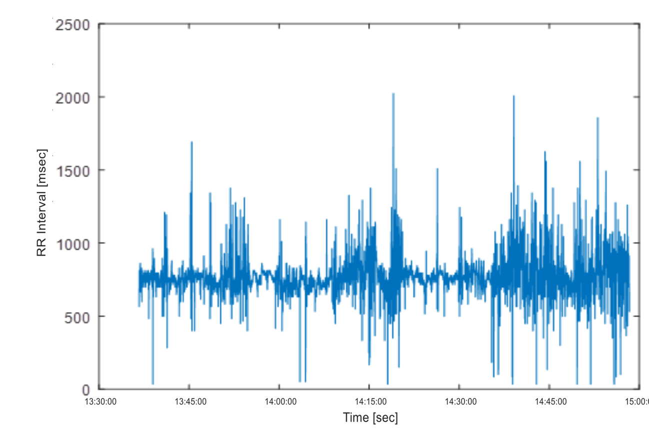
Measurements (both sensors)

- RR intervals
- Accelerometers (x,y,z)

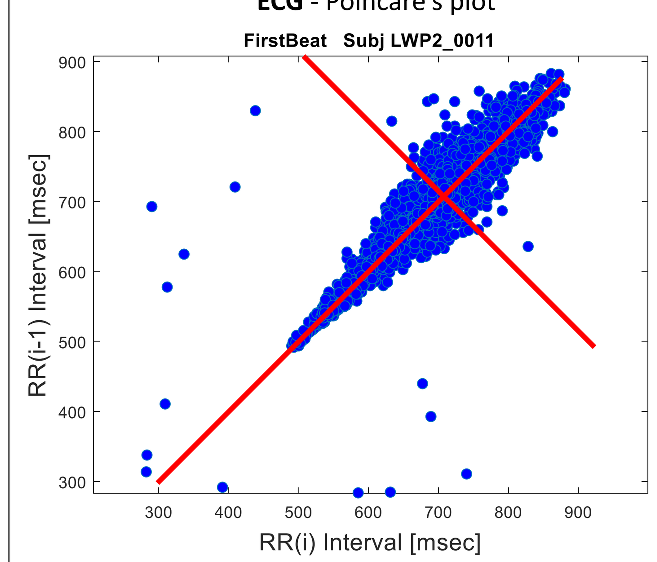
Collected data

Sample data from one participant



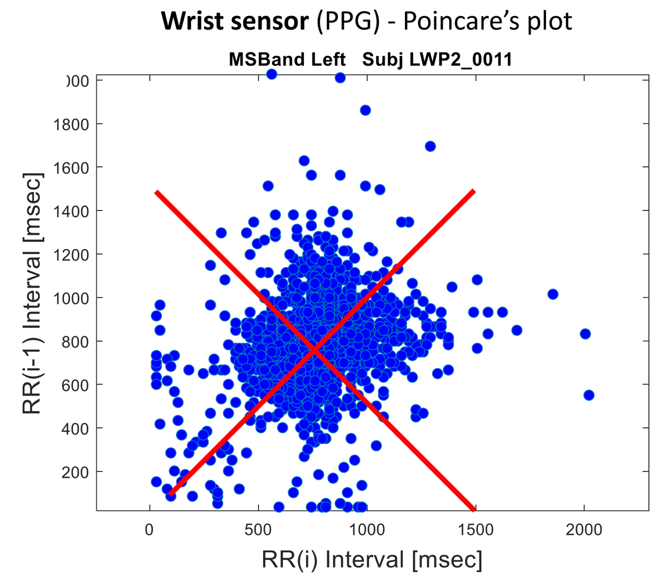


ECG - Poincare's plot



ECG – relatively well behaved data

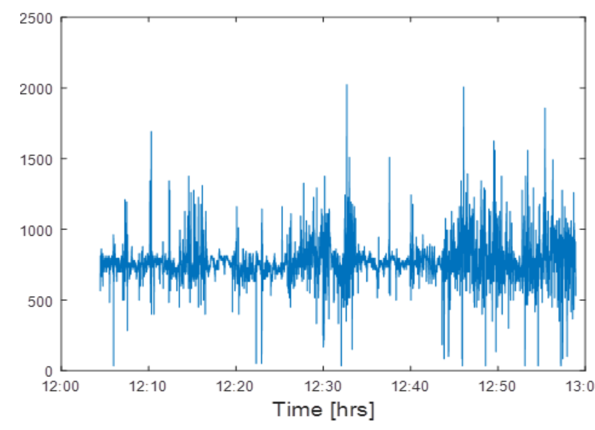
Wrist sensor (PPG) - Poincare's plot

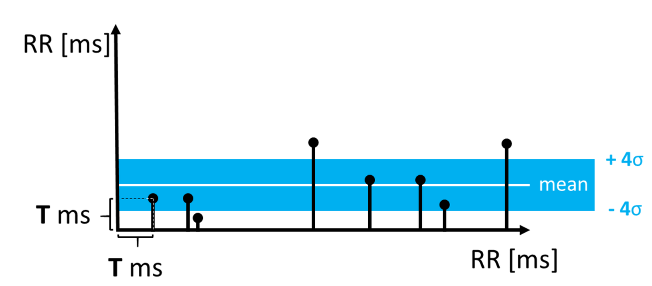


Wrist sensor – noisy data with artefacts

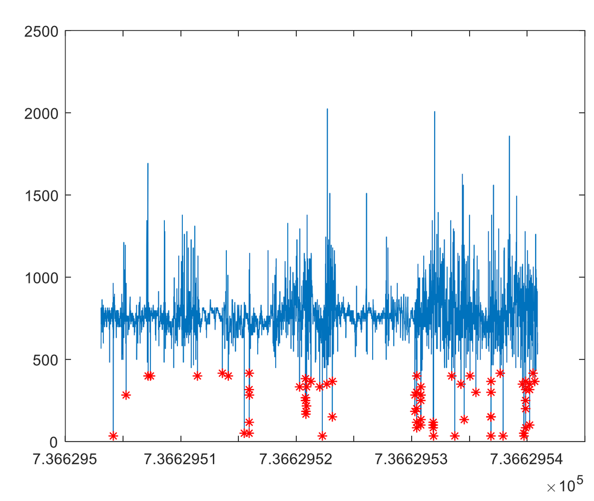
Proposed data cleaning algorithm

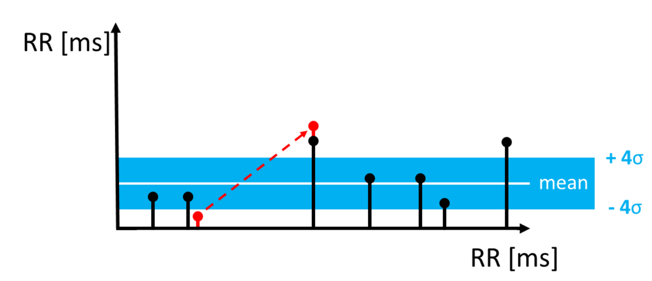
1. Compute mean and standard deviation using robust estimation of mean and variance.





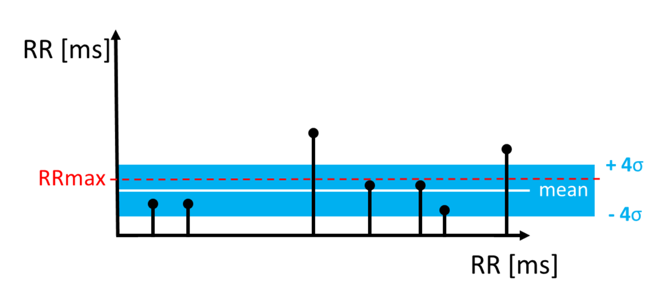
2. Remove "short" RR intervals (RR ≤ $\overline{RR}$ - 4 σ).



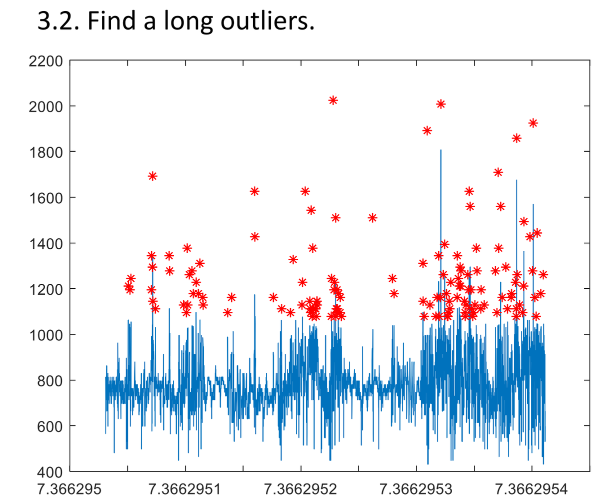


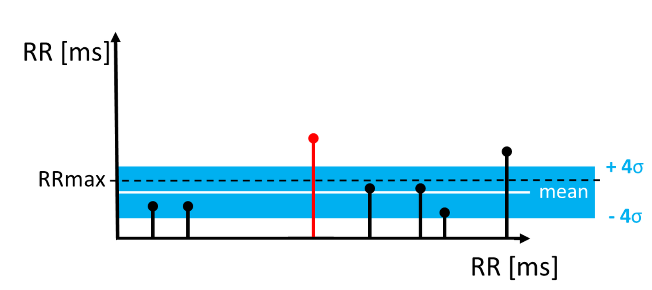
3. Removal of "long" RR intervals and data imputation.

3.1. Set RRmax = mean + 2 σ

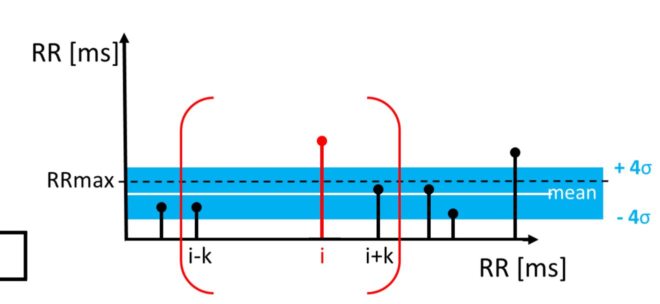


3.2. Find a long outliers.





3.3. Compute the mean of RR intervals in a window from *i-k* to *i+k*, where *i* is the index of the outlier. Start with k = 1.



3.4. Is the mean ≤ RRmax? → No → Increase k by 1.

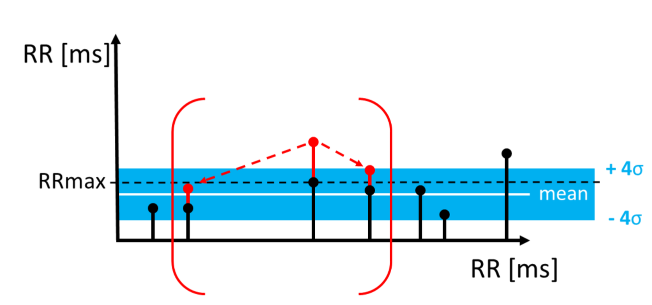
Yes

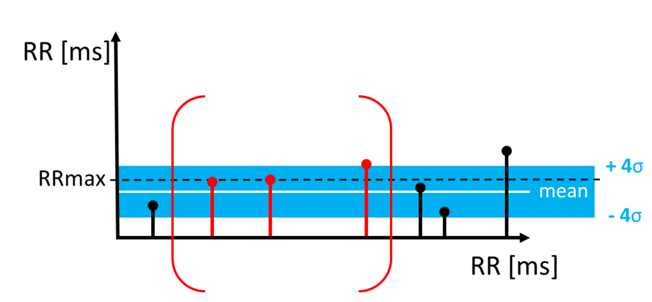
3.5. Set the value of the outlier to RRmax.

Add

$$\frac{\textit{original outlier value} - RR\max}{2k}$$

to the remaining RR intervals in the *[i-k, i+k]* window.





Proposed data cleaning algorithm (continued)

4. Singular Spectrum Smoothing (SSA)
- Generalization of Poincare's method to more than two dimensions
- Useful for smoothing the RR signal and ultimately for imputing missing data and outliers
- Each principal component may account for a particular orthogonal input to HR including noise and activity-related disturbance

4.1 Start with a raw RR interval data sequence

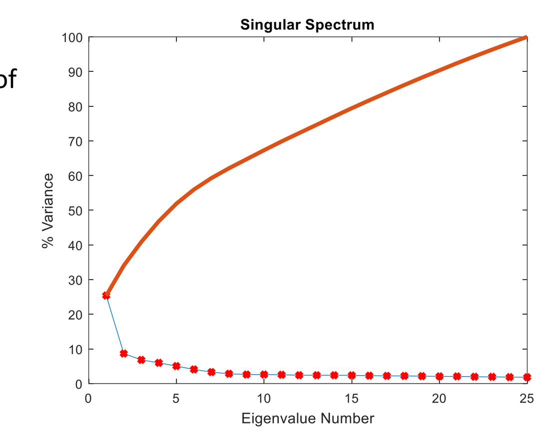
$$R = [\ldots, r_{i-1}, r_i, r_{i+1}, r_{i+2}, \ldots, r_{i+K}]$$

4.2 Generate Toeplitz matrix

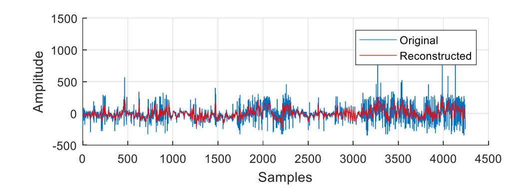
$$A = \begin{bmatrix} r_i & r_{i-1} & r_{i-2} & r_{i-3} & \cdots & r_{i-K+1} \\ r_{i+1} & r_i & & & \cdots & \\ r_{i+2} & r_{i+1} & r_i & & \cdots & \\ r_{i+3} & r_{i+2} & r_{i+1} & r_i & \cdots & \\ \cdots & \cdots & \cdots & \cdots & \cdots & \\ r_{i+K-1} & & & & r_{i+1} & r_i \end{bmatrix}$$

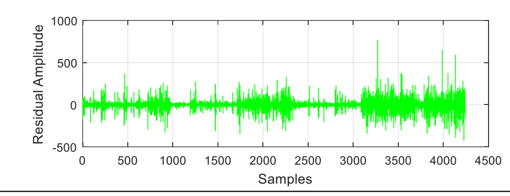
4.3 Compute principal components of A.

4.4 Keep n of K components that account for a significant proportion of variance (> 85%)



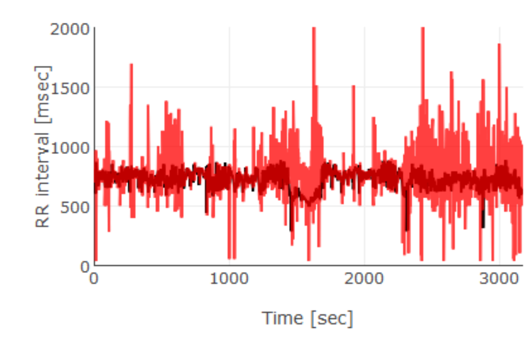
4.5 Reconstruct the cleaned, smooth RR sequence using those components.





Evaluation

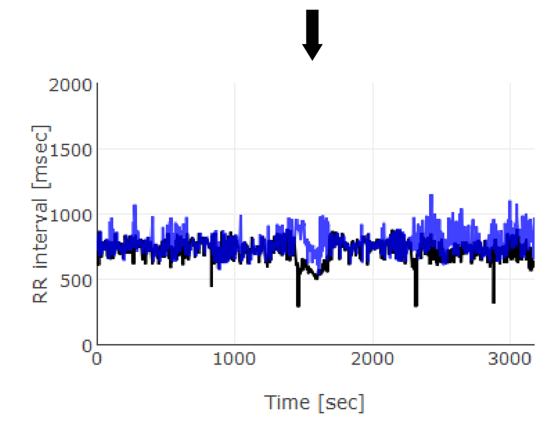
Our algorithm significantly improves agreement between ECG and wrist PPG signals



$\overline{\text{CCC}}_{\text{CLEANED}}$ = .324 > $\overline{\text{CCC}}_{\text{RAW}}$ =.283

(Welch Two Sample t-test, *t* = 19.764, *p* < .001)

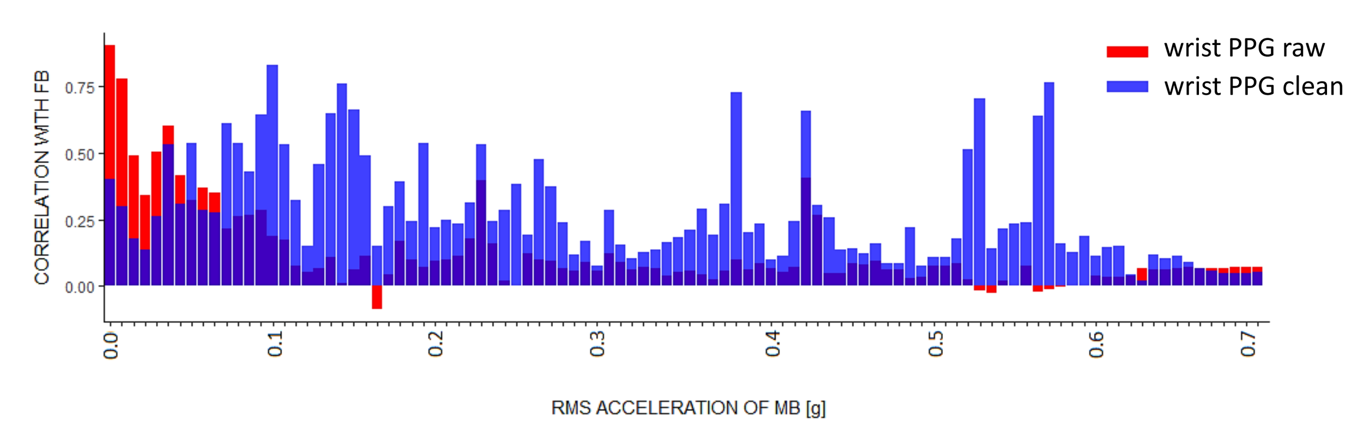
Cleaning



CCC = concordance correlation coefficient

$$\frac{2\rho\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2 + (\mu_x - \mu_y)^2}$$

The algorithm removes motion artifacts without using motion data



1. CCC(ECG, **RAW** SIGNAL) = -.942 * RMSA + Ɛ R^2 = .236
2. CCC(ECG, **CLEAN** SIGNAL) = -.109 * RMSA + Ɛ R^2 = .003

RMSA explains less variance in CCC between ECG and clean signal (eq. 1) than between ECG and raw signal (eq. 2).

Summary of results

1. Coherence between optimally aligned ECG and wrist PPG data is 0.283.
2. We detected that RMSA has a large, negative impact on the agreement between PPG and ECG signals.
3. We developed an algorithm to clean RR data. The algorithm uses Singular Spectrum Smoothing to generalize Poincare's Method to more than two dimensions.
4. Our algorithm removes most motion artifacts and can be used to improve the quality of RR data.

Future work

1. Accelerometry data as a trigger for the algorithm.
2. Near real-time implementation of our data cleaning the algorithm to enable just-in-time interventions based on reliable data.

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